

Multi-objective optimization of an irreversible Stirling cryogenic refrigerator cycle



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ABSTRACT

The main aim of this research article is a parametric demonstration of irreversible Stirling cryogenic refrigerator cycles that includes irreversibilities such as external and internal irreversibilities. In addition, through this study, finite heat capacities of external reservoirs are considered accordingly. To reach the addressed goal of this research, three objective functions that include the input power of the Stirling refrigerator, the coefficient of performance (COP) and cooling load (R_L) have been involved in optimization process simultaneously. The first aforementioned objective function has to minimize; the rest objective functions, on the other hand, have to maximize in parallel optimization process. Developed multi objective evolutionary approaches (MOEAs) based on NSGA-II algorithm is implemented throughout this work. Moreover, cold-side's effectiveness of the heat exchanger, hot-side's effectiveness of the heat exchanger, heat source's heat capacitance rate, heat sink's capacitance rate, temperature ratio (T_h/T_c), temperature of cold side are assigned as decision variables for decision making procedure. To gain a robust decision, different decision making approaches that include TOPSIS, LINMAP and fuzzy Bellman–Zadeh are used. Pareto optimal frontier was determined precisely and then three final outputs have been gained by means of the mentioned decision making approaches.

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1. Introduction

Stirling engine producing low temperature stream, is one of the crucial refrigeration cycle approaches. More description about coefficient of performance (COP) of the refrigeration systems are presented in Ref. [1]. Stirling engine producing low temperature stream also have relevant outputs [1] for the COP of the refrigeration systems.

Leff and Teeters [2] have mentioned that since there is no 'normal peak' in these systems, the straight-forward Curzon–Ahlborn [1] determination will not cover for the reversed Carnot cycle. The Lagrangian approach of unknown multiplier has been utilized by Blanchard [3] to determine the endoreversible Carnot heat

pump's COP operating at lowest input power for a specific heating load. Recently, the efficiency of other refrigeration cycles such as Carnot, Brayton, Stirling and Ericsson has been investigated, by employing the context of the finite time thermodynamics approach [4–9], the criteria of ecological [10–17] and thermo-economic model [18–21] for various working situations.

Finite time thermodynamic (FTT) is one of the basic methods to analyze thermodynamic systems, though the Carnot cycle's endoreversible approach has been presented and progressed for 20 years from 1950s and 1970s [22]. The FTT approaches are utilized through the actual apparatus and processes optimization, related to finite-time and finite-size limitations [23]. In recent years, utilizing FTT concepts for the optimization and evaluate of heat engines and refrigeration systems for various objectives optimizations have made considerable advance [24–30]. Hints for the optimum design of different actual refrigerators have prepared by these developments.

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$$Q_h = T_h \Delta S = C_H(T_{H2} - T_{H1})t_H = U_H A_H (LMTD)_H t_H \quad (1)$$

$$Q_c = T_c \Delta S = C_L(T_{L1} - T_{L2})t_L = U_L A_L (LMTD)_L t_L \quad (2)$$

where entropy change denotes $\Delta S = nR \ln \lambda$, and λ stands for the volume ratio and n denotes the mole number of the working fluid. C_L ; C_H and t_L ; t_H refer to the source/sink reservoirs heat capacitance rates and times of heat addition/rejection, H1 and L1 represent hot-side and cold-side, correspondingly. $U_H A_H$ and $U_L A_L$ indicate the products of area and overall heat transfer coefficient and $(LMTD)_H$ and $(LMTD)_L$ denote the log mean of the difference between temperatures on sink-side and source-side, correspondingly, expressed as:

$$(LMTD)_H = \frac{(T_h - T_{H1}) - (T_h - T_{H2})}{\ln \left(\frac{(T_h - T_{H1})}{(T_h - T_{H2})} \right)} \quad (3)$$

$$(LMTD)_L = \frac{(T_{L1} - T_c) - (T_{L2} - T_c)}{\ln \left(\frac{(T_{L1} - T_c)}{(T_{L2} - T_c)} \right)} \quad (4)$$

Generally, these cycles do not states the situation of complete regeneration, So it is favorable to involve the losses of regenerator that is related to the difference of temperatures between the two mentioned isothermal processes as supposed by previous researches in Refs. [14–16],

$$\Delta Q_R = nC_v(1 - \varepsilon_R)(T_h - T_c) \quad (5)$$

n denotes the mole of the working fluid. C_v denotes the working fluid's specific heat capacity through the processes of the regenerative in unit of mole, ε_R represents the regenerator effectiveness's.

Thanks to the irreversibility impact of the finite heat transfer, the regenerative time have to finite, alike to the above mentioned isothermal processes [12–16], and comes to following expression:

$$t_R = t_3 + t_4 = 2\alpha(T_h - T_c) \quad (6)$$

In which α stands for the proportionality constant, is not depend on the difference of temperatures; however, relates on the characteristics of the regenerative mater. Therefore, the total cycle time t_{cycle} expressed as follow [12–16]:

$$t_{cycle} = (t_H + t_L + t_R) \quad (7)$$

To take into account all of the above mentioned irreversibilities, the net value of the released heat to the sink and absorbed heat from the source are determined by following expressions [9,48]:

$$Q_H = Q_h - \Delta Q_R \quad (8)$$

$$Q_L = Q_c - \Delta Q_R \quad (9)$$

As known for any experts of engine systems, the power input, cooling load and the COP are the most crucial variables of any refrigerator. By executing the above formulations, following formulas can be developed for the power input, cooling load, and cooling COP as following as [9,48]:

$$P = \frac{(Q_H - Q_L)}{t_{cycle}} \quad (10)$$

$$R_L = \frac{Q_L}{t_{cycle}} \quad (11)$$

$$COP_L = \frac{R_L}{P} \quad (12)$$

Dedicated to the thermodynamics second law for irreversible cycles, following formulation should be considered

$$\frac{Q_c}{T_c} - \frac{Q_h}{T_h} < 0 \quad (13)$$

Or

$$\frac{Q_c}{T_c} = \phi \frac{Q_h}{T_h} \quad (14)$$

In which ϕ denotes the irreversibility factor and is lower than one for an actual cycle. So, from Eqs. (6)–(14), following expressions can be developed:

$$P = \frac{x - \phi}{\left(\frac{x}{\varepsilon_H C_H (x T_c - T_{H1})} \right) + \left(\frac{\phi}{\varepsilon_L C_L (T_{L1} - T_c)} \right) + b_1(x - 1)} \quad (15)$$

$$R_L = \frac{\phi - F_1(x - 1)}{\left(\frac{x}{\varepsilon_H C_H (x T_c - T_{H1})} \right) + \left(\frac{\phi}{\varepsilon_L C_L (T_{L1} - T_c)} \right) + b_1(x - 1)} \quad (16)$$

$$COP_L = \frac{\phi - F_1(x - 1)}{x - \phi} \quad (17)$$

$$x = \frac{T_h}{T_c} \quad (18)$$

$$b_1 = \frac{2\alpha}{nR \ln \lambda} \quad (19)$$

$$F_1 = \frac{C_v(1 - \varepsilon_R)}{R \ln \lambda} \quad (20)$$

4. Multi-objective optimization with EA

4.1. Optimization via EA

Genetic algorithm was developed by Holland (1960) in order to involve the mechanisms of biological evolvement into computer code and further optimization process [37,46]. Genetic algorithms (GAs) handle a repetitive, stochastic search approach to determine an optimal route and mimic in a simplified manner principle of biological evolution (Fig. 2). In this study, GA is subset of evolutionary approach is used to obtain the Pareto frontier. This approach is a robust optimization method for nonlinear issues [34–37,46]. To determine a ranking between the obtained routes of a multi-objective optimization issue, optimization of Pareto is the vital key, till to figure out whether a route is actually one of the prior feasible solutions [46]. NSGA-II algorithm as a multi objective optimizer has been executed till to figure out the Pareto frontier from the GA. In Refs. [34–37,40] more about evolutionary algorithms have been presented.

4.2. Objective functions, limitations and decision parameters

The main objectives of the current communication are the system's input power (P), the coefficient of performance (COP), and the cooling load (R_L) denoted by Eqs. (15)–(17), correspondingly.

Following decision parameters have been involved in the current communication:

T_c : Temperature of cold side

x : Temperature ratio $\left(\frac{T_h}{T_c} \right)$

C_H : Heat source's capacitance rate

C_L : Heat sink's capacitance rate

ε_L : Effectiveness of the cold-side heat exchanger

ε_H : Effectiveness of the hot-side heat exchanger

However the above suggested decision parameters can be changed throughout the optimization process, it should be varied within the practical or feasible range. Owing to this fact, following

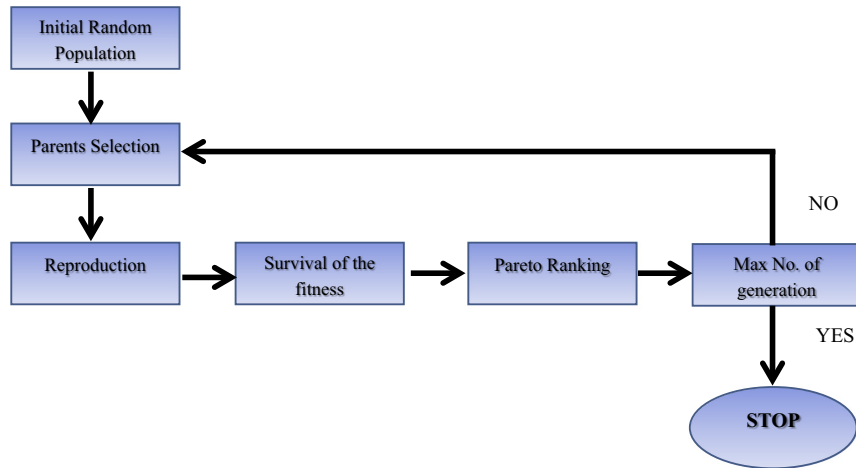


Fig. 2. Chart Box of the multi-objective optimization executed in the current communication [36,37,40].

limitations have been considered for solving the referred objective functions [8,9,13,16,48]:

$$0.5 \leq \varepsilon_H \leq 0.8 \quad (21)$$

$$0.5 \leq \varepsilon_L \leq 0.8 \quad (22)$$

$$235 \leq T_c \leq 240 \text{ K} \quad (23)$$

$$600 \leq C_H \leq 1000 \quad (24)$$

$$600 \leq C_L \leq 1000 \quad (25)$$

$$1.3 \leq x \leq 1.4 \quad (26)$$

5. Decision-making through the multi-objective optimization

Process of making a decision for indicating the prior optimum route from practical outputs is needed through multi-objective optimization process. There are a number of methods for process of making decision in decision issues. To determine a prior optimum output from the Pareto frontier, these methods can be utilized. Before making any decision, objective space scales and dimensions have to unify while dimensions of different objectives might be different through multi-objective optimization issue. Accordingly, objectives vectors would be non-dimensionalized before the decision-making process. Various techniques of non-dimensionalization employed for making a decision such as Euclidean non-dimensionalization, and fuzzy non-dimensionalization.

5.1. Non-dimensionalization methods

5.1.1. Euclidean non-dimensionalization

If the objectives matrix for different solutions of the Pareto frontier is represented by F_{ij}^n where i stands for the index for each route on the Pareto frontier and j denotes the index for mentioned objectives in objective space. In this method, a non-dimensionalized objective, F_{ij}^n , is represented as following as:

$$F_{ij}^n = \frac{F_{ij}}{\sqrt{\sum_{i=1}^m (F_{ij})^2}} \text{ for minimizing and maximizing objectives} \quad (27)$$

5.1.2. Fuzzy non-dimensionalization

Throughout this technique, a non-dimensionalized objective, F_{ij}^n , is expressed as following:

$$F_{ij}^n = \frac{F_{ij} - \min(F_{ij})}{\max(F_{ij}) - \min(F_{ij})} \text{ to maximize objectives} \quad (28a)$$

$$F_{ij}^n = \frac{\max(F_{ij}) - F_{ij}}{\max(F_{ij}) - \min(F_{ij})} \text{ to minimize objectives} \quad (28b)$$

In the current study, robust, familiar and usual type of decision-making techniques that includes TOPSIS, LINMAP and fuzzy Bellman–Zadeh, techniques are applied to gain final optimum solution is selected using these three methods. The LINMAP and TOPSIS methods utilize Euclidean non-dimensionalization while the Bellman–Zadeh technique executes the fuzzy non-dimensionalization and the following sections explain the mentioned decision-making techniques.

5.2. Decision making techniques

5.2.1. Bellman–Zadeh decision-making technique

Prior optimum solution defined by Bellman–Zadeh approach can be indicated by intersection point between restrictions and fuzzy criteria meantime suggested by corresponding membership function. In Bellman–Zadeh technique, a membership function's matrix is determined in which column illustrates the objective fuzzy membership function. In addition, rows of the mentioned matrix present values of the membership functions for each obtained outcomes from the Pareto frontier. Put it in other way, the number of matrix columns represents the number of proposed objectives and the number of matrix rows represents the number of obtained outcomes relied on the Pareto optimum frontier. Detail for method of definition for the membership function has been stated in Refs. [36,37,47]. For the proposed solution, the fuzzy membership function for each outcome is a group at the lower value limit of the all objectives membership functions. In this regard, a membership vector is determined who its components are the least objectives membership function for each outcome. Totally, the highest value of these lower limits i.e. a component of the membership vector with highest magnitude of membership function is considered as a great optimum outcome. Let me rephrase that, throughout making a decision by executing Bellman–Zadeh fuzzy technique, an upper limit of lowest bound of objectives membership function is considered as the prior optimum solution. In Refs. [36,37,47] more details are presented.

5.2.2. LINMAP decision-making technique

A criterion of LINMAP decision making technique should be defined here that called “ideal point” who addressed to the data point on the Pareto frontier which each mentioned objective is optimized either singly. It would be stressed here that it is impossible to gain optimum objectives by utilizing single objective optimization because we have different objectives that optimized

simultaneously. Due to this fact, location of the ideal point is not on the Pareto frontier. LINMAP technique selects the optimum solution based on the distances of output on the Pareto frontier from the ideal point. In other words, the solution that has lowest deviation from the ideal point is considered as an optimum route through executing LINMAP method. More explanations of the LINMAP technique can be found in previous works of Ahmadi and colleagues [36,37,47].

5.2.3. TOPSIS decision-making technique

Throughout TOPSIS technique another criterion should be added which defined as “non-ideal point” that refers to worst values of the proposed objectives in the objective area. Keep in mind that same as previous decision making methods, ideal point is another important criterion for selecting optimum solution. So, distances between the solutions gained from the ideal and non-ideal data points are the selection criteria for determining optimum solution through executing TOPSIS method. Owing to this fact, throughout the TOPSIS technique the optimum solution has a maximum distance from non-ideal point and on the hand has a minimum deviation from ideal point. Further descriptions about TOPSIS technique have been given in Ref. [47].

6. Result and discussion

The coefficient of performance (COP) and the cooling load (R_L), are maximized simultaneously and the input power is simultaneously minimized by executing optimization approach that performs according to the NSGA-II procedure.

In this respect, multi objective optimization is executing with the previously mentioned objective functions whose are formulated in Eqs. (15)–(17) limitations that are proposed with Eqs. (21)–(26).

Decision parameters through the optimization algorithm are the cold side temperature, temperature ratio ($\frac{T_h}{T_c}$), heat source capacitance rate, heat sink capacitance rate, effectiveness of the cold-side heat exchanger, effectiveness of the hot-side heat exchanger.

Following Stirling cryogenic refrigerator specifications are considered to have same standard with previous literature [9], $T_{H1} = 300$ K, $T_{L1} = 250$ K, $\varepsilon_R = 0.9$, $\lambda = 2$, $n = 1$, $R = 4.3$ (J mol⁻¹ K⁻¹), $C_v = 15$ (J mol⁻¹ K⁻¹), $\phi = 0.8$, $\alpha = 10^{-5}$ (s K⁻¹).

Pareto optimal frontier for three mentioned objective functions that include input power, cooling load and the coefficient of performance are represented in Fig. 3. Besides, selected data points thanks to the decision making approaches are depicted in Fig. 3.

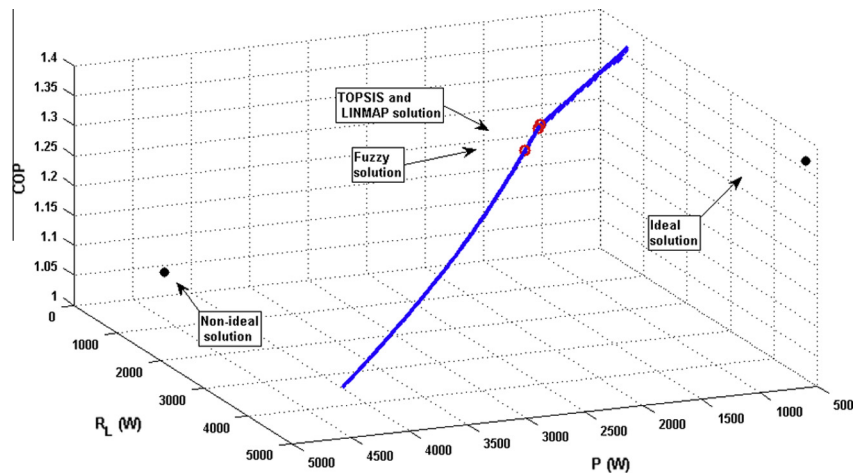


Fig. 3. Pareto optimal frontier in objectives' space.

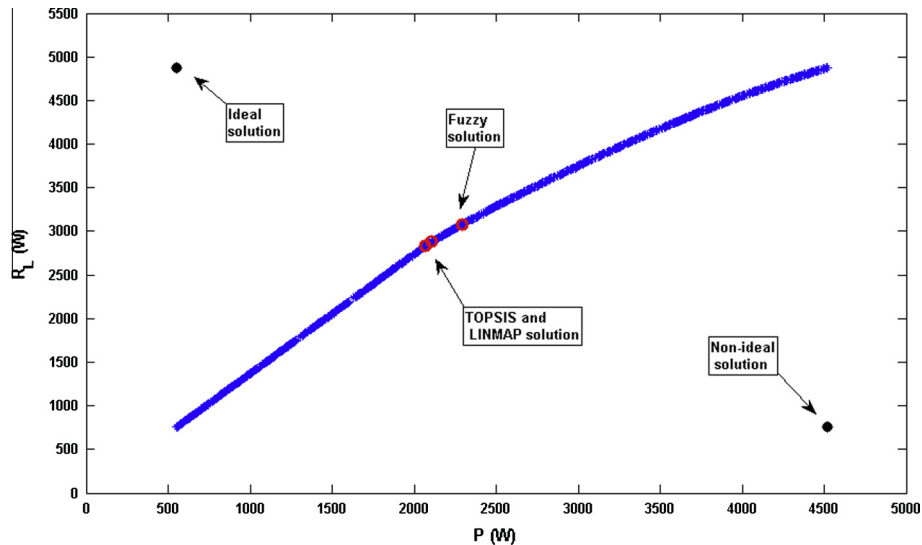


Fig. 4. Pareto frontier (Pareto optimal solutions) for the input power versus cooling load using NSGA-II.

As it is shown Fig. 3 optimum results of TOPSIS and LINAMP methods are very close together and are more suitable than FUZZY method results, due to less power input and higher COP. Power input and COP are more effective than RL, on system performance.

Pareto optimum frontier for cooling load and input power which are two objective functions are shown in Fig. 4. In addition, selected data points thanks to the decision making approaches are depicted in Fig. 4. As the system is more sensitive to the amount of input power and this sensibility is less to RL, results of TOPSIS and LINAMP methods are better than FUZZY method results. One of the optimization goals is to minimize the power input, which it leads to better performance of the system.

Pareto optimum frontier for input power and the coefficient of performance whose are two objective functions are shown in Fig. 5. Moreover, selected data points thanks to the decision making approaches are depicted in Fig. 5. The less input power and the higher COP lead to better system performance. According to this, results of

TOPSIS and LINAMP methods are optimum in comparison with FUZZY method results which is displayed in Fig. 5.

Pareto optimum frontier for cooling load and the coefficient of performance that are two objective functions are shown in Fig. 6. Furthermore, selected data points thanks to the decision making approaches are depicted in Fig. 6.

Figs. 7–12 demonstrate the scattered distribution of the design variables. These plots can provide better vision of variation of the design variables from the Pareto frontier. The distribution of C_H for the optimum data on Pareto front is demonstrated in Fig. 7 meanwhile the minimum and maximum boundaries of the variables are illustrated. Furthermore, Fig. 8 represents the variables distribution for the optimum data on Pareto front for C_L . In addition, the upper and lower boundaries of the addressed parameters are illustrated. Also, the variation of these addressed parameters for the optimal points on Pareto front for ε_H over population are depicted in Fig. 9 whereas upper and lower limit of ε_H referred to 0.5 and 0.8, respectively. The same analogy was employed for ε_L .

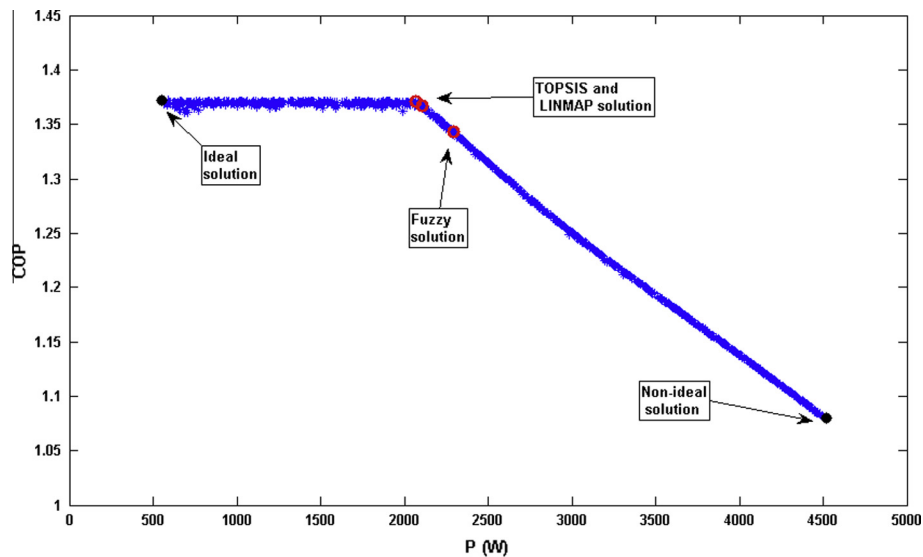


Fig. 5. Pareto frontier (Pareto optimal solutions) for the input power versus the coefficient of performance using NSGA-II.

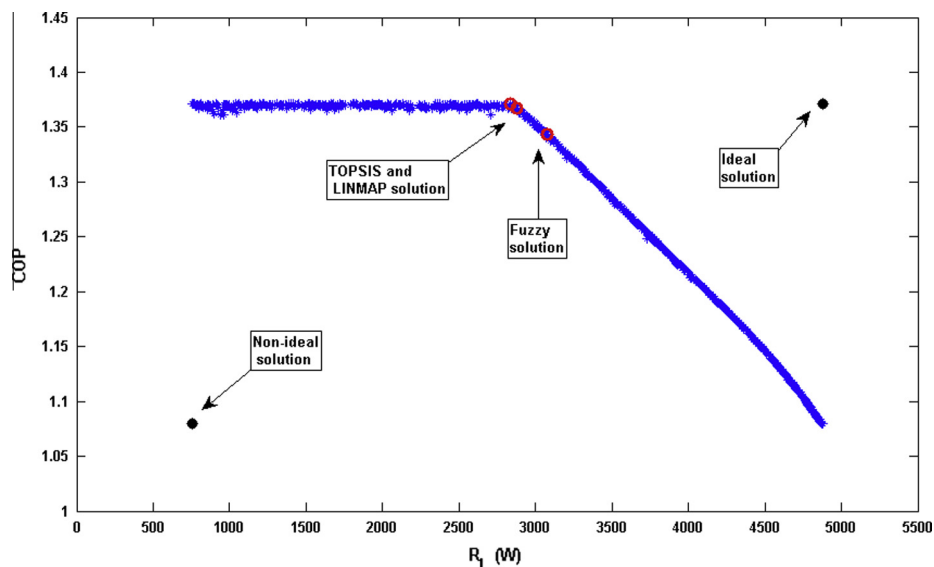


Fig. 6. Pareto frontier (Pareto optimal solutions) for the cooling load versus the coefficient of performance using NSGA-II.

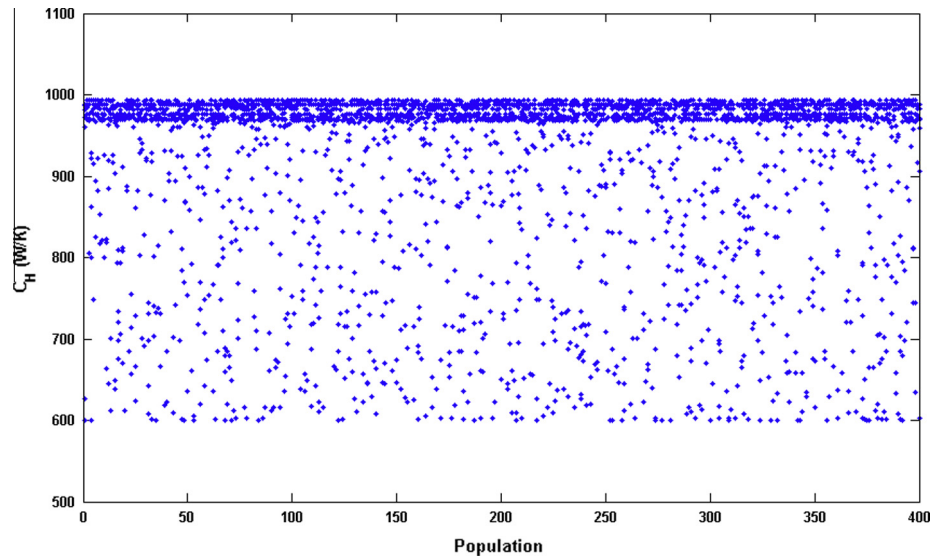


Fig. 7. The variation of C_H on the Pareto front for the optimum points.

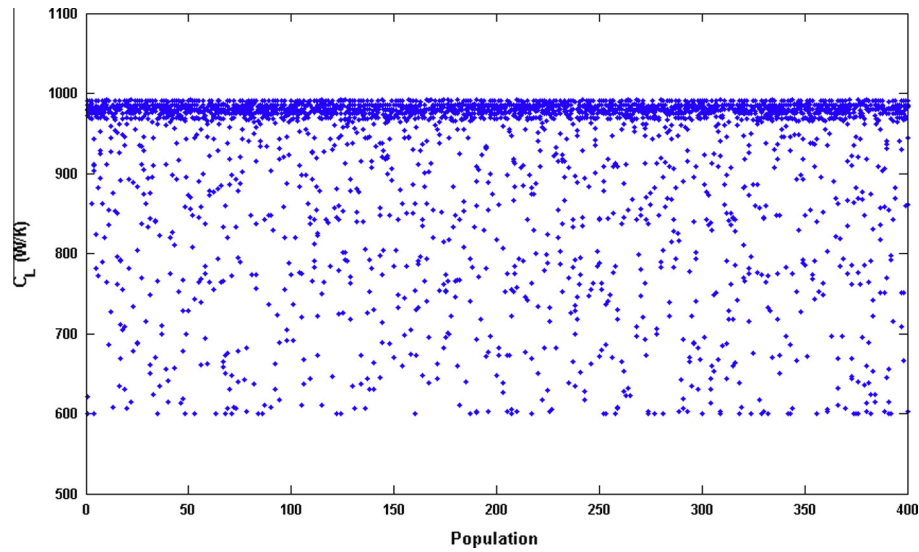


Fig. 8. The variation of C_L on Pareto front for the optimum points.

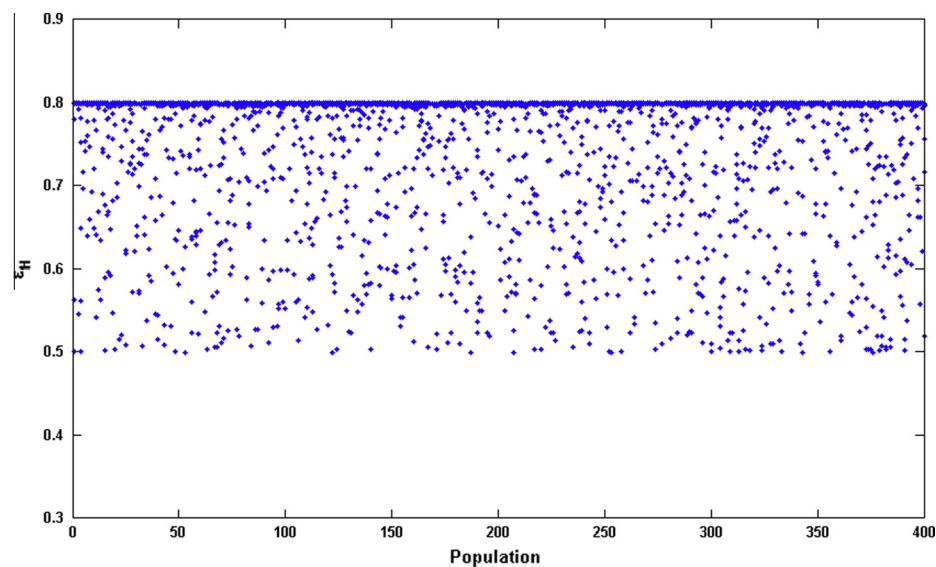


Fig. 9. The variation of e_H on Pareto front for the optimum points.

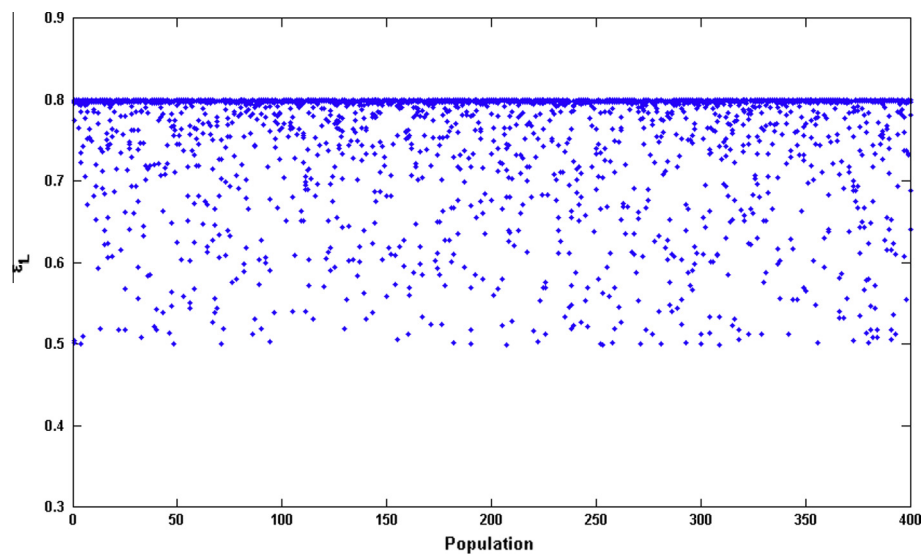


Fig. 10. The variation of ϵ_L on Pareto front for the optimum points.

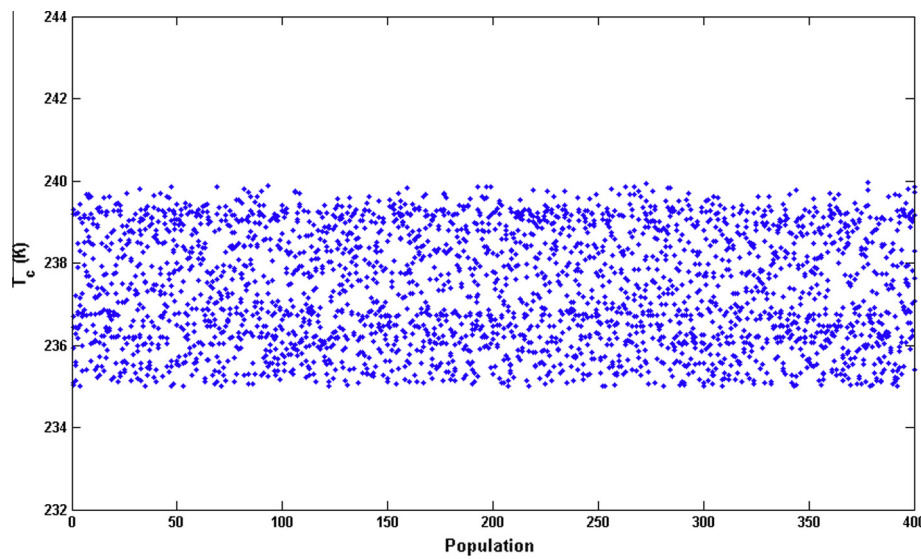


Fig. 11. The variation of T_c on Pareto front for the optimum points.

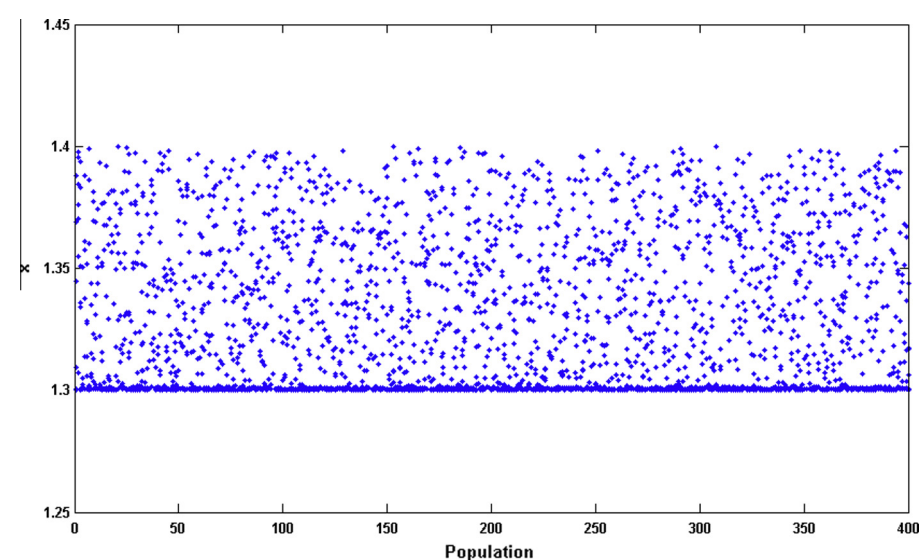


Fig. 12. The variation of x on Pareto front for the optimum points.

Table 1

Comparison of the final optimum solutions of this work (multi objective-multi variable) with relevant results gained in Refs. [9,48] (single objective-single variable optimization) ($n=1$, $C_v = 15$ (J mol⁻¹ K⁻¹), $R = 4.3$ (J mol⁻¹ K⁻¹), $\lambda = 2$).

Decision making method	Decision variables						Objectives		
	ε_H	ε_L	T_c (K)	x	C_H (W/K)	C_L (W/K)	P (W)	R_L (W)	COP
TOPSIS	0.79427	0.79931	239.784	1.30002	986.888	990.969	2067.701	2835.817	1.371483
LINMAP	0.79671	0.79758	239.849	1.30116	987.897	990.986	2105.365	2879.062	1.367488
Fuzzy	0.79919	0.79919	239.737	1.30811	987.796	990.983	2290.827	3077.963	1.343604
Ref [9]	0.8	0.8	240.5	1.40	1000.0	1000.0	4423.765	4414.133	0.998
Ref [48]	0.8	0.8	–	1.90	1000.0	1000.0	2710	2370	0.875

Table 2

Error analysis of the results gained from the three aforementioned decision making approaches in the basis of MAPE.

Decision making method	TOPSIS			LINMAP			Fuzzy		
	P	R_L	COP	P	R_L	COP	P	R_L	COP
Max error %	6.77	11.78	5.51	5.43	10.47	5.81	5.66	10.35	5.56
Average error %	2.78	8.07	5.44	2.70	7.62	5.41	2.81	8.01	5.36

dedicated to this fact, the assortment of the mentioned parameters for the optimum data on Pareto front for the addressed parameter over population is illustrated in Fig. 10 and upper and lower restrictions of ε_L are 0.5 and 0.8, correspondingly.

Fig. 11 depicts the variation of T_c for the optimum points on Pareto front though the lower and upper magnitudes of the referred parameters are marked. Finally, variables distributions for the optimum points on Pareto front for x over population are exhibited through Fig. 12 and upper and lower ranges of x eluded to 1.3 and 1.4, respectively.

The optimal outputs obtained from three mentioned decision making methods (Bellman–Zadeh, TOPSIS, and LINMAP) that include decision parameters and objective functions are demonstrated throughout Table 1.

Table 1 compares solutions gained from our suggested decision making techniques with relevant solutions found in Ref. [9,48]. Where Table 1 demonstrated outputs gained from Bellman–Zadeh, TOPSIS, and LINMAP decision making techniques for the Stirling cryogenic refrigerator and outcomes illustrated by Tyagi [9,48].

7. Error analysis

To perform error analysis on the mentioned approaches, mean absolute percentage error (MAPE) was utilized properly. For this purpose, 30 different executions were utilized to gain optimum solutions by mentioned decision making techniques (that include TOPSIS, LINMAP and Bellman–Zadeh). The results obtained from error analysis are demonstrated in Table 2. According the MAPE values reported in Table 2, LINMAP approach has a better solution for P and R_L in contrast with other decision making methods; however, fuzzy method has a great solution for COP draw in parallel with the rest decision making techniques.

8. Conclusions

In this study, to calculate input power, the cooling load (R_L) and the coefficient of performance (COP) of the Stirling cryogenic refrigerator, FIT approach was employed. The aforementioned parameters of the Stirling cryogenic refrigerator were simultaneously involved throughout multi-objective optimization process that includes following decision variables: 1 – The effectiveness of the cold-side heat exchanger (ε_L), 2 – the hot-side heat exchanger's effectiveness (ε_H), 3 – heat sink's heat capacitance rate (C_L), 4 – heat source's heat capacitance rate (C_H), 5 – cold side's temperature (T_c) and 6 – temperatures ratio (x). It is worth to mention that NSGA-II

algorithm was also executed to evolve the performance of the multi objective evolutionary algorithm used. After running mentioned optimization algorithm, the Pareto optimal frontier throughout objectives space was calculated. On the basis of the Pareto optimal frontier gained, an optimum solution was acquired by the three decision making approaches introduced previously that categorized in fuzzy, LINMAP and TOPSIS methods. Throughout this communication, it is proved this fact that the multi objective optimization method eventuates to favorable design of the Stirling cryogenic refrigerator draw a parallel with the single objective optimization method that conducted in previous literature [9,48].

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